A Work Project, presented as part of the requirements for the Award of a Master Degree in Finance from the NOVA – School of Business and Economics.

Illiquidity Shocks and the Size Effect:

An Event Study of Liquidity Crises.

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A Project carried out on the Master in Finance Program, under the supervision of:

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Date: 5th January 2017

1. **Abstract**

This paper empirically investigates the impact of liquidity on stock returns during liquidity crises. An event study approach is employed to analyse the behaviour of stock returns around periods of crisis. The focus is set on the different effect of liquidity shocks on large and small/medium caps. Tests for the presence of abnormal returns show that small/medium stocks are negatively affected by crashes in market liquidity, while blue chips performance is not significantly influenced by the crises. The abnormal returns for small caps occur immediately after the liquidity crises and the impact generally lasts for the 15 following trading days. From a *buy-and-hold* perspective the deviation from the predicted performance can account for up to -1.7%.

Keywords: *Liquidity, Event Study, Crisis, Company Size*

2.**Introduction & Literature Review**

This research provides an empirical analysis of stock returns during times of crisis in aggregate liquidity; the main objective is to assess the impact of the shocks on securities prices and to test if this impact is captured by asset pricing models. For this purpose, the major liquidity crises are investigated in an event study framework.

The event study approach is commonly employed in the study of corporate events such as mergers or earnings announcements. This methodology allows to analyse whether a particular set of events is consistently able to influence stocks returns, and to make them deviate from their normal/expected performance. Therefore, the event study approach represents a useful tool in identifying the consequences of liquidity crises.

Liquidity is commonly defined in the financial literature as the ease by which an asset can be bought or sold in the market without incurring in significant losses originating from a price difference or from transactions costs.

The direct and indirect costs of illiquidity need always to be taken into account when making investing decisions due to their ability to significantly impact the performance of an investment strategy. Furthermore, this liquidity-related risk is likely to increase during episodes of crisis. For that reason, liquidity and its impact on asset prices have been widely investigated in recent years.

A number of measures for liquidity have been developed and the general consensus among researchers suggests that there exists a certain degree of correlation between stocks returns and market liquidity, and that this correlation is indeed priced in the market.

Amihud & Mendelson (1986) adopted the bid-ask spread as measure of liquidity, this figure represents the difference between the price at which an investor is able to buy and to sell a specific security in the open market.

Their findings show that average returns are an increasing function of illiquidity. The economic rationale is that if a security is more sensitive to shocks in liquidity, investor will be less prone to buy it, and hence they will require higher expected returns.

Pastor & Stambaugh (2003) analyse market-wide liquidity and test its significance as a state variable in asset pricing models. Employing a measure of liquidity that reflects price impact of order flows, they find that stock *liquidity betas* (measured as stocks' sensitivity to innovations in aggregate liquidity) play an important role in asset pricing.

Further support to the relevance of liquidity is provided by Y.Hamiud (2002), whose empirical study tests for the existence and statistical significance of *illiquidity premiums*. His findings are in line with the previous financial literature, as his empirical tests suggest that there exists a positive relation between illiquidity and ex-ante stock excess return. His results also show how small caps returns are on average more sensitive to changes in illiquidity than large cap, providing also an empirical explanation of the so called *small firms effect,* which is not entirely captured by common asset pricing models.

Other studies focus on how the sensitivity to changes in liquidity varies over time and across different economic states. Fujimoto & Watanabe (2004) considered two different state of the world, one associated with low liquidity betas and the other with high liquidity betas. Through this comparative analysis they show that the degree of uncertainty regarding future assets demand significantly influences stock returns and their sensitivities to shocks in aggregate liquidity.

The event-study method for the study of liquidity has already been employed by Cao & Petrasek (2013). Their work studies the effectiveness of market models around periods of illiquidity crises. Their findings reveal that the main asset pricing models are, on average, not able to provide good estimates of expected returns in these context. The empirical test that they performed show that *illiquidity betas* (sensitivity of stock returns to aggregate liquidity) are strongly correlated with the *abnormal returns* observed in these situations. They also investigate information asymmetry as a source of liquidity risk, and their statistical analysis shows that more transparent companies on average outperform their peers during liquidity crises.

This study will follow a similar procedure, but the focus is set on the different outcomes of the shock according to companies' size, measured by their market capitalization. The economic intuition is that shocks in aggregate liquidity should alter the market perception of illiquid stocks. The effect of a collapse in market-wide liquidity creates uncertainty around illiquid securities due to the reduced ability to liquidate those assets. This uncertainty can translate in a drop in prices and in the observation of *abnormal returns*. Liquidity risk should also have a more significant impact on small caps rather than on large caps, since for an illiquid stocks the risk of not being able to find a buyer or a seller is considerably higher than for blue chips. As shown by Y.Amihud (2002) small caps are, on average, more sensitive to swings in market-wide liquidity than larger public corporations, this should reflect also in stock returns.

The impact of liquidity crisis is a crucial factor which needs to be taken into consideration when managing portfolios of stocks. If a portfolio has a high exposure to illiquidity risk its long term performances might be hijacked by abnormal negative returns around liquidity shocks. Therefore, analysing the significance and the magnitude of the anomalous returns has important implications for portfolio management purposes.

3.**Data and Methodology**

3.1 **Dataset and Subsamples**

The data sample for this empirical study covers the period from 2005 to 2015 and consists of stocks prices with a daily frequency from the S&P500 index, as well as the index itself and the daily volume of trades. These observations have been retrieved from Bloomberg. Estimates for the SMB HML and Momentum are also employed in this thesis, these data have been retrieved from the Kenneth French website. The framework applied to this study is based on the methodology for event study suggested by MacKinlay (1997).

The analysis will be performed on two subsamples of stocks, representing the two extreme deciles of stocks ranked by companies size, which represent small caps and large cap stocks respectively, as suggested by Y.Amihud (2002) and by Fujimoto & Watanabe (2006).

In order to build the two sub-samples, we consider only the stocks for which the entire set of observations is available, then this sub-set of stocks are ranked by market cap as in the end of 2015 (*Appendix – Table (1)*), out of 505 stocks in total, we will consider only 411, therefore the first subset includes the top 40 stocks by market cap and the second includes the bottom 40 stocks.

3.2 **Illiquidity Measure and Event Dates**

The events that this paper aims to study are the days in which the most significant liquidity shocks occur. These dates are not explicitly identified like, for instance, earnings announcements or IPOs dates; therefore, there is the need to define a measure of illiquidity, and to study the dynamic of this measure in order to identify the extreme events in its fluctuation.

As suggested by Y.Amihud (2002) and Acharya&Pedersen (2005), the price impact or ILLIQ measure is employed throughout this study. The authors argue that stock illiquidity can be defined as the effect that each dollar of trade has on the price of the underlying security. In this case this concept is applied to an equity index therefore, a good estimate of the price impact of the volumes of trade can be computed as the ratio of its daily return in absolute value to the trading volume on each trading day.

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{VOL_{i,t}} \qquad (1)$$

Daily log-returns are calculated for S&P500 index on a daily basis, and using daily observation for the volumes of trade the *ILLIQ* values are computed for the same timeframe and for the entire sample (*Appendix – Graph (1)*).

The second step is to identify the dates in which the liquidity crises happen, these dates are defined as the most extreme observations of aggregate illiquidity, which represent also the moments of lowest degree of liquidity in the market.

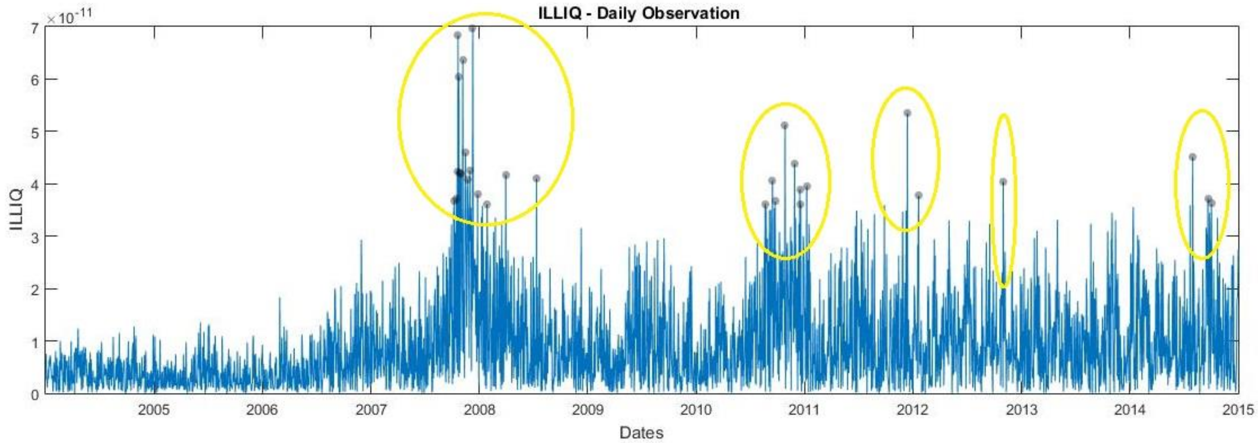
In order to find these events in the fluctuations of illiquidity, we need to generate the daily series for this measure. Using the computed daily observation of ILLIQ a ranking is built and the top 40 observations have been extracted (out of 2769 observation). These 40 dates identify the days in which illiquidity reached its highest values (see *Appendix* - *Table (2)*).

When ranking the observations, a clustering effect is clearly noticeable in the dynamics of illiquidity, this implies that very low levels of liquidity are concentrated around certain periods of time. As shown in *Graph (1)* (see appendix) the financial crisis of 2008 and the sovereign debt crisis of 2011 are easily recognizable.

As suggested by *MacKinlay* (1997) the event windows or the estimation periods of an event should not overlap with other events object of the study, since the price changes produced by an event may affect the stocks expected returns for the following periods. It is crucial for the purpose of the event study to identify a unique event date for each crisis. Overlapping estimation periods and event windows may produce biased results; therefore, the event dates are reduced to the five observations in which the illiquidity measure reaches its peaks.

The top 40 observations in the time series of ILLIQ are grouped into 5 main illiquidity clusters (highlighted in *Graph (2)*) and each cluster the highest ranked observation within the group defines an event date for the event study.

Graph (2) – ILLIQ top 40 & Illiquidity Clusters



The event study will analyse the performance of the two subsets of stocks around the crises dates, displayed in *Table (3)*.

Table (3) – Event Dates

Event Dates
01/12/2008
10/10/2011
23/11/2012
10/10/2013
08/07/2015

3.3 **The Event Study Settings and the CAAR Method**

For each event date and for each stock, the following measures are computed for the two subsamples of stocks:

$$\textit{Abnormal Returns} \rightarrow AR_{i,t} = R_{i,t} - E[R_{i,t} | \Omega_{i,t-1}] \qquad (2)$$

$$\textit{Cumulative Abnormal Returns} \rightarrow CAR_{i,(T_1,T_2)} = \sum_{t=T_1}^{T_2} AR_{i,t} \qquad (3)$$

$$\textit{Cumulative Average Abnormal Return} \rightarrow CAAR_{(T_1,T_2)} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,(T_1,T_2)} \qquad (4)$$

The abnormal returns defined in *Equation (2)* measure the difference between the observed return and the expected return, *AR* coincides with the ex-post observed residuals for the considered asset pricing model ($\varepsilon_{i,t}$), therefore they capture the price movements not explained by the underlying asset pricing model. If there exists an identifiable pattern in the series of *ARs* surrounding the event dates, the events object of the study are likely to significantly affect the behaviour of the stocks for which the analysis is performed.

In order to identify those patterns in *ARs* and to test their statistical significance it is useful to aggregate the *ARs* observed around the event date and for a defined period of time, the *Event Windows*. The cumulative abnormal returns defined in *Equation (3)* are calculated as the sum of the abnormal returns over the event window, and it provides an estimate of the overall direction and size of the stock behaviour during the crises.

The CAR measure aggregates the AR per each event dates, but in order to test the significance of the events objet of the study a further level of aggregation is needed.

Considering 40 stocks and 5 event dates, each subsample will produce 200 CARs, these measures can be averaged, and their average produces the cumulative average abnormal returns or CAAR (as shown in *Equation (4)*).

In order to identify the above mentioned measures, we also need to specify:

- An asset pricing model,
- An estimation window
- An event window

The asset pricing model used throughout this study is the four-factor model proposed by Carhart (1997) in which stocks returns are explained by the market factor, by the small minus big factor, by the high minus low factor, as suggested by Fama&French (1992), plus the Carhart momentum factor.

$$r_{i,t} = r_f + \beta_{1,i} * r^e_{MKT,t} + \beta_{2,i} * SMB_t + \beta_{3,i} * HML_t + \beta_{4,i} * MOM_t + \varepsilon_{i,t} \qquad (5)$$

In order to perform the event study, the OLS estimates for the above model are computed for all the stocks taken into account. For the purpose of this empirical research, an estimation windows of 250 days is considered, meaning that the Carhart four-factor model for period *t* is estimated using the observations starting in *t-250*. This estimation window provides good estimates for the model coefficients and it also guarantees that the estimation periods for each event object of the study do not overlap with other illiquidity crises, since this may involve a biased estimation for the CARs, as explained by MacKinlay(1997).

Once the expected returns for each stock are computed, the abnormal returns can be determined and these abnormal returns are aggregated for eight different event windows which last respectively 25, 20, 15, 10, 7, 5, 3 and 2 periods.

The Average CAR is calculated through the aggregation of the cumulative abnormal returns across stocks and events.

Using the above measures, we can test the significance of the abnormal return through a cross-sectional t-test with the following set of hypotheses:

$$\begin{cases} H_0: CAAR_{(T_1,T_2)} = 0 \\ H_1: CAAR_{(T_1,T_2)} \neq 0 \end{cases} \qquad (6)$$

Under the null hypothesis the impact of the event on the stock returns is not statistically significant, since, on average, the abnormal returns around the event dates is not consistently different from zero.

The test statistic is computed as follows:

$$t - stat = \frac{CAAR_{(T_1,T_2)}}{\hat{\sigma}_{CAAR_{(T_1,T_2)}}} \qquad (7)$$

Where the standard deviation of the cumulative average abnormal returns is:

$$\hat{\sigma}_{CAAR_{(T_1,T_2)}} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left[CAR_{i,(T_1,T_2)} - CAAR_{(T_1,T_2)}\right]^2} \qquad (8)$$

The cumulative abnormal returns and the CAARs are computed and tested over all the event windows, this allows to analyse the timing of the abnormal returns and their dynamic over time.

3.4 **The BHAR Method**

An alternative measure of the deviation of the stock returns from its normal performances is the buy and hold abnormal return (or BHAR).

The BHAR as proposed by Jay R. Ritter (1991) and Barber & Lyon (1997) represents the difference between the observed returns of an investment over a certain holding period around the event date, and the normal return that the same investment was expected to generate for the same length of time, considering the underlying asset pricing model.

The BHAR measure provides a clearer representation of the investor experience during the liquidity crisis since it captures the actual unexpected impact of the liquidity shock over a certain holding period.

$$BHAR_{i,e}(t_1, t_2) = \prod_{t=t_1}^{t_2}(1 + R_{i,t}) - \prod_{t=t_1}^{t_2}(1 + E[R_{i,t}]) \qquad (9)$$

In order to assess the statistical significance of the BHAR, it is averaged across stocks and events as shown in *Equation (10)*.

$$Average\big(BHAR(t_1, t_2)\big) = \frac{1}{N}\sum_{i=1}^{N} BHAR_i(t_1, t_2) \qquad (10)$$

As suggested by Johnson (1978) the buy-and-hold abnormal return is positively skewed, therefore, the results of a standard t-test would be biased, for this reason Johnson developed a skewness adjusted t-test that takes into account the peculiarity of the BHAR's distribution.

The t-statistic is computed as follows:

$$T_{SkewnessAdj} = \sqrt{N} * \left[t + \frac{1}{3}\hat{\lambda}t^2 + \frac{1}{6N}\hat{\lambda}\right] \qquad (11)$$

Where t and $\hat{\lambda}$ are defined as:

$$t = \frac{Average\big(BHAR(t_1, t_2)\big)}{\widehat{\sigma_{BHAR}}} \;; \hat{\lambda} = \frac{\left(\sum_{i=1}^{N}\left[BHAR_i(t_1, t_2) - Average\big(BHAR(t_1, t_2)\big)\right]^3\right)}{N * \widehat{\sigma_{BHAR}}} \quad (12)$$

And where $T_{SkewnessAdj}$ follows a t-student distribution, therefore we can employ the Johnson skewness-adjusted t-test to test the null hypothesis of zero average BHAR (*Equation (13)*).

$$\begin{cases} H_0: Average(BHAR) = 0 \\ H_1: Average(BHAR) \neq 0 \end{cases} \qquad (13)$$

As previously done for analysis of CAARs the Johnson skewness-adjusted t-test is applied to several holding periods which last respectively 25, 20, 15, 10, 7, 5, 3 and 2 periods.

Finally, after the above mentioned tests have been performed for both subsamples, the results are qualitatively compared to assess the different effect of illiquidity for the subsets of small/medium caps stocks against the subset of large caps.

According to the financial literature and to the general economic consensus regarding the impact of illiquidity, the expectations are to observe negative abnormal returns for both subsets of stocks and to withstand a more significant deviation for what concerns small/medium caps if compared to large stocks. Moreover, the negative performance of stocks should not be anticipated by the markets since liquidity crises are highly unpredictable, therefore the ARs should occur starting from *t+1*. The duration of the impact should depend on the specific of the events and is not possible to predict it a priori.

4.**Results**

4.1 **The CAAR Approach – First Subsample**

Graph (3) shows the observed cumulative average abnormal returns for the subsample of small and medium stocks over the 25 period after the liquidity crises date.

Graph (3): CAAR 1st Subsample

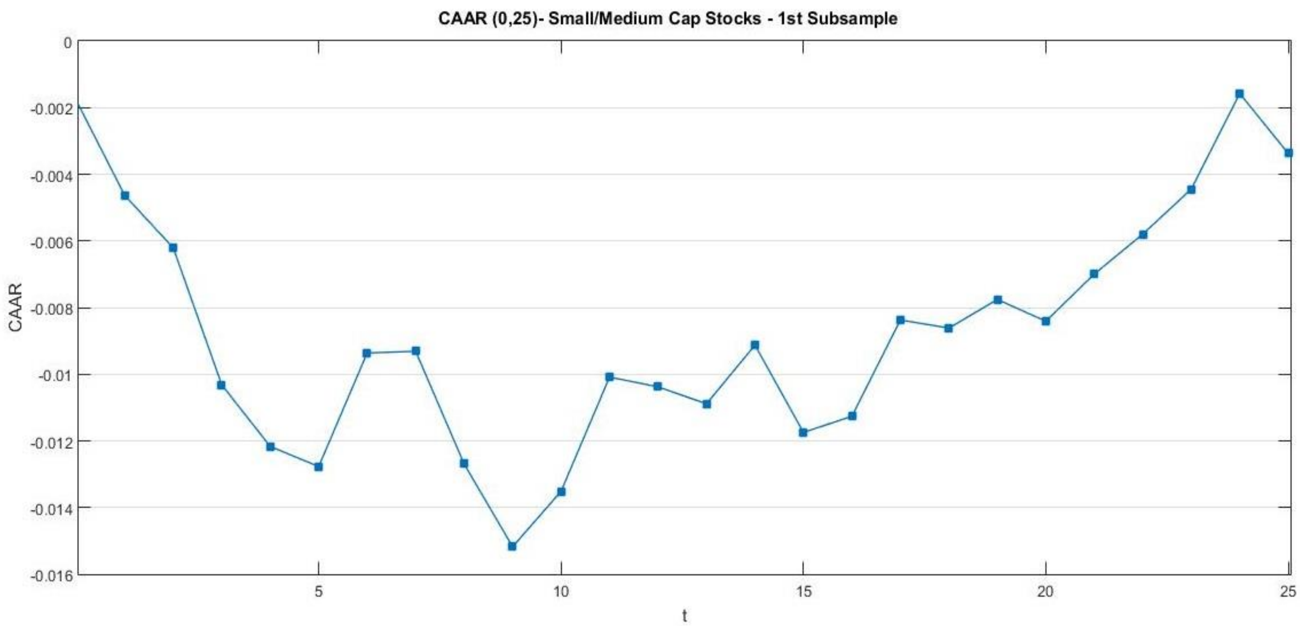


Table (4) presents the value for the cross-sectional t-test performed on the CAARs for the first subsample of stocks and considering several event windows. T-statistics and the relative p-values are calculated. Moreover, the number of positive and negative CAARs across stocks and event dates are displayed and compared.

Considering the t-statistics and the p-values shown in *Table (4)* it is possible to reject the null hypothesis stated in *Equation (6)*. For the considered set of events and asset pricing models the CAARs are consistently different from zero, therefore, the events object of the study are likely to meaningfully affect the returns of smaller cap stocks. Taking into account a confidence interval of 1.00% the CAARs are statistically significant for event windows up to 10 periods after the event date, and up to 15 periods for a confidence interval of 2.5%.

Table (4): Cross Sectional t-Tests – CAAR Method – 1st Subsample

Date	CAAR	Pos : Neg	Negative	Cross Sectional T-Test	Prob
(0,25)	-0.34%	97 : 103	51.50%	-0.5237	0.6005
(0,20)	-0.84%	90 : 110	55.00%	-1.4528	0.1463
(0,15)	-1.17%	94 : 106	53.00%	-2.3248	0.0201
(0,10)	-1.35%	87 : 113	56.50%	-3.2256	0.0013
(0,7)	-0.93%	85 : 115	57.50%	-2.6063	0.0092
(0,5)	-1.28%	82 : 118	59.00%	-4.1276	0.0000
(0,3)	-1.03%	75 : 125	62.50%	-4.0845	0.0000
(0,2)	-0.62%	83 : 117	58.50%	-2.8384	0.0045

Most of the Average ARs after 15 periods from the event dates are positive (see *Table (5)*), suggesting that the impact of the liquidity crises starts vanishing after *t+15*.

In order to test whether the market anticipates the liquidity crises cross sectional t-test are performed also for event windows starting before the event dates, event windows for (-10,25) and (-20,25) were considered. As expected, due to the highly unpredictability of the liquidity crises, the AR generated before the event are not statistically significant as shown in *Table (6)* and in *Table (7)* (see appendix).

4.2 **The CAAR Approach – Second Subsample**

The same methodology is employed to analyse the performance of large caps around the liquidity crisis days. *Table (5)* displays the results of the cross sectional t-test and the CAAR (0,25) for the second subset of stocks.

The observed abnormal returns are initially positive, and turn negative only after 5-6 trading days, meaning that right after the event large caps tend to outperform expectations. Despite this initial trend, the observed CARs revert quickly to negative values and they stay negative for the following periods.

Table (5): Cross Sectional t-Tests – CAAR Method – 2nd Subsample

Date	CAAR	Pos : Neg	Negative	Cross Sectional T-Test	Probability
(0,25)	-0.0119	84 : 116	58.00%	-1.7582	0.0787
(0,20)	-0.0061	81 : 119	59.50%	-1.5049	0.1324
(0,15)	-0.0018	96 : 104	52.00%	-0.5075	0.6118
(0,10)	-0.0015	89 : 111	55.50%	-0.5082	0.6113
(0,7)	-0.0005	88 : 112	56.00%	-0.2139	0.8306
(0,5)	0.0024	103 : 97	48.50%	1.1139	0.2653
(0,3)	0.0033	106 : 94	47.00%	1.8544	0.0637
(0,2)	0.0022	100 : 100	50.00%	1.4434	0.1489

Even if the dynamic of abnormal returns seems to follow a precise pattern, the observed CAARs are not statistically significant for any of the event windows taken into account and considering a wider confidence interval of 5%.

The results of the cross sectional t-tests suggest that the liquidity crises do not systematically affect the returns of large cap stocks. The observed performance of blue chip after the crises does not consistently deviate from the expected returns generated by the asset pricing model taken into account.

These findings differ from the initial expectations of this research, in fact, according to economic theory and to the previous financial literature, all stocks should suffer from drops in aggregate liquidity. The empirical evidence of this study suggest that large caps are not largely influenced by shocks in aggregate liquidity.

4.3 **BHAR Method – First Subsample**

Graph (5) and *Table (6)* present the main results of the BHAR analysis for the first subsample of stocks.

The average BHAR measure allows to analyse the impact of liquidity crises on stocks performances, since it represent the actual abnormal return that an investor would face for each considered holding period.

Graph (5) – Average BHAR (0,25) – 1st Subsample

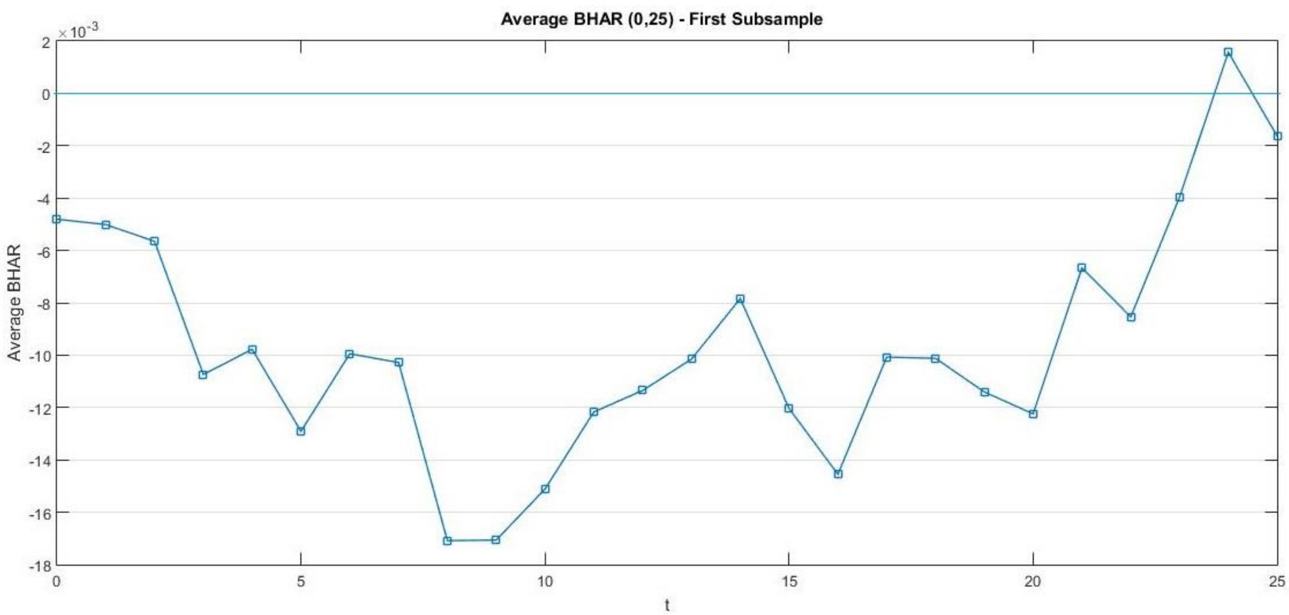


Table (6) – BHAR Skewness Adjusted T-Test – 1st Subsample

Date	BHAR	Pos : Neg	T-Statistic	Skewness Adjusted T-Statistics	Prob
(0,25)	-0.0016	100 : 100	-0.2286	-0.2279	0.8197
(0,20)	-0.0122	89 : 111	-1.6975	-1.7245	0.0846
(0,15)	-0.012	88 : 112	-2.0148	-2.0748	0.038
(0,10)	-0.0151	82 : 118	-2.988	-3.0998	0.0019
(0,7)	-0.0103	86 : 114	-2.5235	-2.5422	0.011
(0,5)	-0.0129	84 : 116	-3.0052	-3.1702	0.0015
(0,3)	-0.0107	80 : 120	-2.7569	-3.0532	0.0023
(0,2)	-0.0057	90 : 110	-2.0155	-2.1263	0.0335

The results for the cross-sectional t-test previously described are confirmed by the analysis of buy-and-hold abnormal returns. As expected, small and medium size stocks generally underperform expectations around liquidity crises.

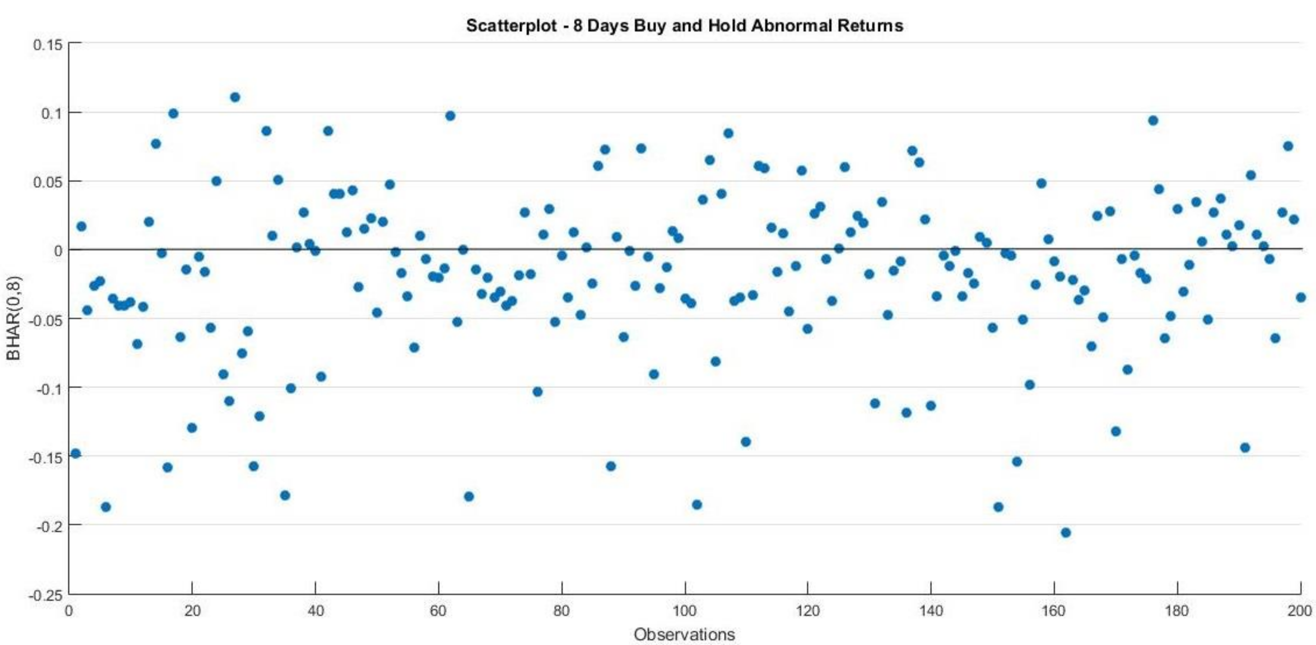
For event windows up to 15 periods the average BHAR is consistently negative and from a statistical point of view, the buy and hold returns are significantly different from zero (considering a 5% confidence interval).

The cumulative performance for an investment in the considered small cap stocks would produce a return 0.5% lower than expected for a 2 days holding period, and the unexpected negative return will be on average 1.7% for a holding period of 8 days.

If we consider the observed distribution of abnormal returns, with a 2 days holding period, the unpredicted return produced by an investment in small stocks would be lower than -5% for more than 1 out of 10 observations (see appendix *Graph (6)*).

The risk of holding small cap stocks during liquidity crises is even more significant when analysing the observed BHARs for an 8 days holding period as displayed in *Graph (7)*.

Graph(7) - Scatterplot 8 Days Buy and Hold Abnormal Returns



Considering this event window, 20% of the observed BHAR are below -5% and 10% of the observations are below -10%, the downside risk is considerably high if compared to the positive observed buy and hold abnormal returns, where only 1 out of 200 observations generates BHAR higher than 10%.

4.4 **BHAR Method – Second Subsample**

Table (7) presents the main results of the BHAR approach for the second subsample of stocks.

Table (7) – BHAR Skewness Adjusted T-Test – 2nd Subsample

Date	BHAR	Pos : Negative	Skewness Adjusted T-Statistic	p-value
(0,25)	-0.0026	99 : 101	-0.523	0.601
(0,20)	0.0011	96 : 104	0.2349	0.8143
(0,15)	0.0035	98 : 102	0.8228	0.4106
(0,10)	0.0023	100 : 100	0.6497	0.5159
(0,7)	0.0019	101 : 99	0.7387	0.4601
(0,5)	0.0036	99 : 101	1.5867	0.1126
(0,3)	0.0039	103 : 97	2.1737	0.0297
(0,2)	0.0023	97 : 103	1.3191	0.1871

Like previously observed for the CAAR analysis, also from a buy and hold point of view, the liquidity crises do not affect consistently the returns of large cap stocks. The same pattern identified for the cumulative abnormal return is observed for the average BHAR.

In the periods following the event dates large stocks tend to outperform expectations, delivering a buy-and-hold return 0.39% higher than expected over the same timeframe. The average BHAR for the holding period (0,3) is also significant from a statistical perspective (considering a 5% confidence interval), suggesting that the events, in the very short run, affects positively the stock performances.

As previously mentioned this effect can be associated with a flight-to-liquidity phenomenon, meaning that if the investors expect a possible crash in the market, they would choose to seek positions in more liquid stocks, since this increase their ability to liquidate the exposure in the near future.

The remaining BHAR are not statistically significant, suggesting that on average liquidity crises do not generate unexpected swings in large stock cumulative performances.

5. **Conclusions**

This study provides further empirical evidence in the analysis of liquidity crises. Small and large caps behaviour is investigated for the period between 2005 and 2015. The results generated by the two subsamples shows substantial differences.

Small and medium stock returns seem to be highly affected by the events considered; illiquidity shocks tend to negatively affect small caps which are underperforming the expectations. This impact, on average, is not captured by common asset pricing models, and it generally arises immediately after the event, and lasts for the following 15 trading days.

The implications for investors can be significant since the downside risk of holding small caps increases steeply in periods of liquidity crisis, confirming the prominent role played by liquidity in portfolio management decisions.

For what concerns large caps, the impact of illiquidity is much milder, the abnormal returns are not statistically significant for most of the considered event windows, and the overall impact of a liquidity crisis is not always negative. In fact, the initial reaction of large caps produces positive CAARs and BHARs which quickly turn negative in the following periods. What arises from this analysis is that, for what concerns large caps the Carhart four factor asset pricing model is able to efficiently predict returns, also when market illiquidity reaches extreme levels.

The initial tendency to outperform expectations can be related to the investors' preference for liquid asset in context of liquidity crises and of general uncertainty on the market, therefore an initial shift may originate from portfolios rebalancing. In order to prove this hypothesis further research and tests would be necessary.

References

Acharya, V.V., Pedersen, L.H., 2005, Asset Pricing With Liquidity Risk, Journal of Financial Economics, Vol 77, pp 375-410

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid–ask spread. Journal of Financial Economics 17, pp 223-249.

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, Journal of Financial Markets, 31-56.

Barber, B.M., Lyon, J.D., 1997, Detecting Long-Run Abnormal Stock Returns: The Empirical Power and Specification of Test Statistics, Journal of Financial Economcs, Vol 43, pp 341-372.

Carhart, M.M., 1997, On persistence in mutual fund performance, Journal of Finance, Vol. 52, pp 57-58.

Cao, C., Petrasek, L., 2013, Liquidity risk in stock returns: An event-study perspective, Journal of Banking and Finance, 72-83.

Fama, E.F., French, K.R, 1992, The Cross-Section of Expected Stock Returns, The Journal of Finance, Vol 47, pp 427-465.

Fujimoto, A., Watanabe, M., 2004, Time-Varying Liquidity Risk and the Cross Section of Stock Returns, Working paper University of Alberta and Rice University.

Johnson, N.J., 1978, Modified T-Tests and Confidence Intervals for Asymmetrical Populations, Journal of the American Statistical Association, Vol 79, pp 536-544.

MacKinlay, A.C., 1997, Event Study in Economics and Finance, Journal of Economic Literature, Vol. XXXV, pp 13-39.

Pastor, L., Stambaugh, R.F., 2003. Liquidity Risk and Expected Stock Returns., Journal of Political Economy, Vol 111, pp 642-685.

Ritter, J.R., 1991, The Long Run Performance of Initial Public Offerings, The Journal of Finance, Vol 46, pp 3-27.

Appendix

Table (1) – Stocks Ranked by Market Cap: First and Tenth Deciles

Top 40	Stocks	Last40	Stocks
1	AAPL UW Equity	411	URBN UW Equity
2	GOOGL UW Equity	410	SWN UN Equity
3	MSFT UW Equity	409	OI UN Equity
4	BRK/B UN Equity	408	CHK UN Equity
5	XOM UN Equity	407	R UN Equity
6	AMZN UW Equity	406	PWR UN Equity
7	GE UN Equity	405	NRG UN Equity
8	JNJ UN Equity	404	DNB UN Equity
9	WFC UN Equity	403	MUR UN Equity
10	JPM UN Equity	402	FLIR UW Equity
11	PG UN Equity	401	PBI UN Equity
12	T UN Equity	400	RRC UN Equity
13	PFE UN Equity	399	LM UN Equity
14	WMT UN Equity	398	PDCO UW Equity
15	VZ UN Equity	397	RIG UN Equity
16	KO UN Equity	396	PBCT UW Equity
17	BAC UN Equity	395	OKE UN Equity
18	DIS UN Equity	394	JEC UN Equity
19	CVX UN Equity	393	FMC UN Equity
20	HD UN Equity	392	AIZ UN Equity
21	INTC UW Equity	391	NFX UN Equity
22	C UN Equity	390	FLS UN Equity
23	MRK UN Equity	389	ZION UW Equity
24	GILD UW Equity	388	TGNA UN Equity
25	PEP UN Equity	387	IRM UN Equity
26	CMCSA UW Equity	386	AVY UN Equity
27	CSCO UW Equity	385	LEG UN Equity
28	IBM UN Equity	384	HP UN Equity
29	AGN UN Equity	383	PKI UN Equity
30	AMGN UW Equity	382	PVH UN Equity
31	BMY UN Equity	381	SPLS UW Equity
32	MO UN Equity	380	NI UN Equity
33	UNH UN Equity	379	PHM UN Equity
34	MCD UN Equity	378	RHI UN Equity
35	CVS UN Equity	377	AIV UN Equity
36	MDT UN Equity	376	ALB UN Equity
37	NKE UN Equity	375	LUK UN Equity
38	BA UN Equity	374	COO UN Equity
39	CELG UW Equity	373	AES UN Equity
40	LLY UN Equity	372	AN UN Equity

Table (2) – ILLIQ Top 40 Observations

Rank	Dates
1	01/12/2008
2	13/10/2008
3	28/10/2008
4	15/10/2008
5	23/11/2012
6	10/10/2011
7	05/11/2008
8	08/07/2015
9	09/11/2011
10	19/11/2008
11	09/10/2008
12	20/10/2008
13	22/10/2008
14	23/03/2009
15	02/07/2009
16	12/11/2008
17	29/08/2011
18	10/10/2013
19	20/12/2011
20	28/11/2011
21	16/12/2008
22	02/01/2013
23	07/10/2008
24	26/08/2015
25	30/09/2008
26	07/09/2011
27	08/09/2015
28	04/08/2011
29	30/11/2011
30	20/01/2009
31	06/09/2012
32	29/06/2015
33	13/11/2008
34	02/01/2009
35	06/11/2008
36	08/08/2011
37	18/12/2014
38	24/11/2008
39	02/09/2011
40	23/08/2011

Table (5) – AARs & CARs – CAAR Method – 1st Subsample

Date	AAR	CAAR
0	-0.00179	-0.00179
1	-0.00285	-0.00464
2	-0.00157	-0.00621
3	-0.00411	-0.01032
4	-0.00185	-0.01217
5	-0.0006	-0.01277
6	0.003408	-0.00936
7	5.16E-05	-0.00931
8	-0.00338	-0.01269
9	-0.00248	-0.01518
10	0.001663	-0.01351
11	0.003428	-0.01009
12	-0.0003	-0.01038
13	-0.00051	-0.01089
14	0.00176	-0.00913
15	-0.00262	-0.01175
16	0.000486	-0.01126
17	0.002888	-0.00837
18	-0.00024	-0.00862
19	0.000858	-0.00776
20	-0.00065	-0.00841
21	0.001416	-0.00699
22	0.001197	-0.0058
23	0.00135	-0.00445
24	0.002868	-0.00158
25	-0.0018	-0.00337

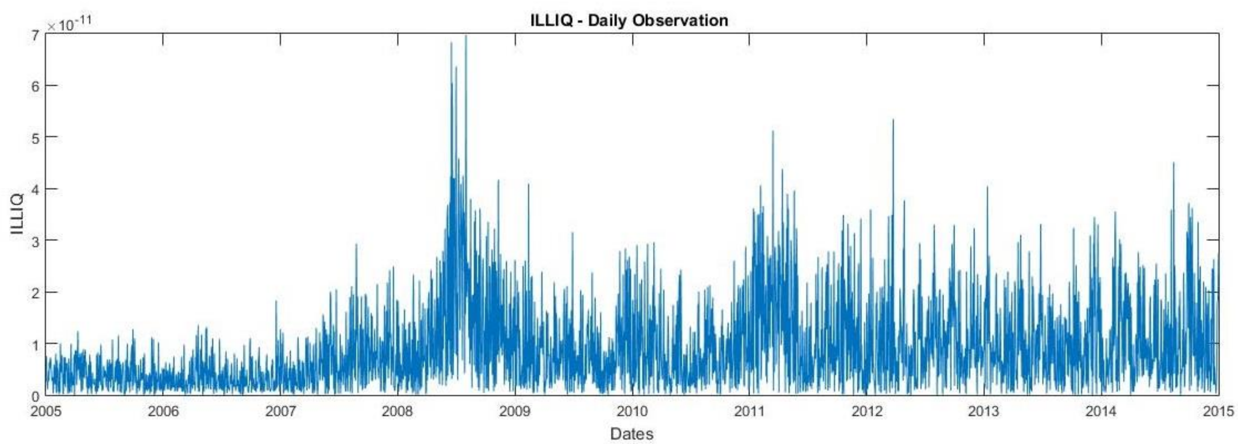
Table (6) – (-10,25) Test for Anticipated Event – Cross Sectional T-Test – 1st Subsample

Date	CAAR	Pos : Neg	Cross Sectional T-Test	Prob.
(-10,25)	0.0034	100 : 100	0.4584	0.6467
(-10,20)	-0.003	93 : 107	-0.4313	0.6663
(-10,15)	-0.0066	89 : 111	-1.0494	0.294
(-10,10)	-0.0088	85 : 115	-1.5443	0.1225
(-10,7)	-0.0052	87 : 113	-0.9865	0.3239
(-10,5)	-0.0091	88 : 112	-1.8407	0.0657
(-10,3)	-0.0074	89 : 111	-1.6023	0.1091
(-10,2)	-0.0031	98 : 102	-0.6991	0.4845

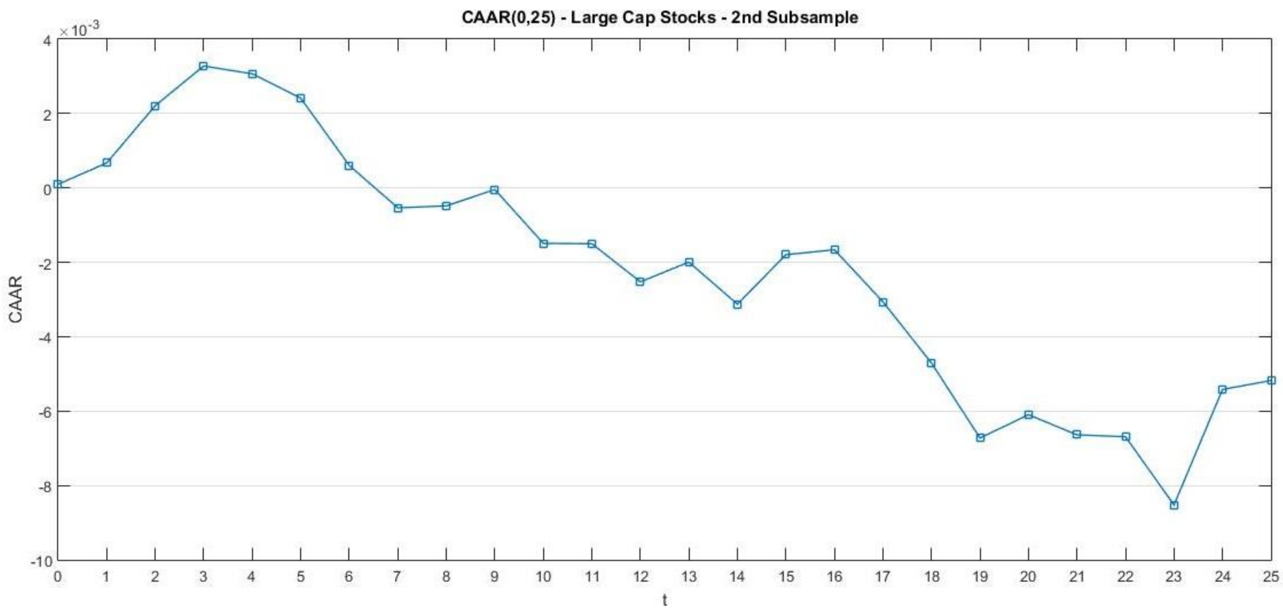
Table (7) – (-20,25) Test for Anticipated Event – Cross Sectional T-Test – 1st Subsample

Dates	CAAR	Pos : Neg	Cross Sectional T-Test	Prob.
(-20,25)	-0.0016	106 : 94	-0.1906	0.8488
(-20,20)	-0.0082	95 : 105	-1.0501	0.2937
(-20,15)	-0.0119	93 : 107	-1.6254	0.1041
(-20,10)	-0.0141	96 : 104	-2.0723	0.0382
(-20,7)	-0.0109	90 : 110	-1.6879	0.0914
(-20,5)	-0.015	98 : 102	-2.4052	0.0162
(-20,3)	-0.0134	93 : 107	-2.2458	0.0247
(-20,2)	-0.0091	90 : 110	-1.5465	0.122

Graph (1) – Daily observation for ILLIQ



Graph (4) – CAARs – Second Subsample



Graph (6) – Scatterplot 2 Days Buy and Hold Abnormal Returns